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Dynamic modeling of causal relationship between energy consumption, CO_2 emissions and economic growth in India

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ABSTRACT

The paper investigates the causality relationships among energy consumption, carbon dioxide (CO_2) emissions and income in India using a dynamic modeling approach. The paper also utilises an innovation accounting method to investigate profiles of the macroeconomic variables persisting from an unanticipated shock in innovation. Our results provide evidence of the existence of bi-directional Granger causality between energy consumption and CO_2 emissions in the long-run but neither CO_2 emissions nor energy consumption causes movements in real income. There is no causality relationship between energy consumption and income in any direction in the long-run implying that India could follow energy conservation and efficiency improvement policies without impeding economic growth. This will allow India to reduce CO_2 emissions without affecting its economic growth and contribute significantly towards combating global warming as well.

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1. Introduction

The anthropogenic carbon dioxide (CO_2), a major green house gas (GHG) emission resulting from combustion of fossil fuels is being considered as one of the most important causes for increasing global warming and causing climatic instability (IPCC) [1]. The GHG emissions seem to aggravate these problems in the current decade (Kaygusuz) [2]. The recently held United Nations Climate Change Conference at Copenhagen in 2009 has attracted

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unprecedented participation by the world leaders to reach a consensus on legal binding of GHG emission reduction to preserve the environment for present as well as future generations and make the economy more sustainable. According to UN [3] the main contributors of total GHG emissions are China (22.30%), United States (19.90%), European Union (14.%), India (5.50), Russia (5.24) and Japan (4.28). The crux of the debate, also in the Cancun 2010 Climate Change Conference, is about how to reduce GHG emissions by high polluting economies without limiting their pace of economic development. This is because of the contradiction between a commonly held view that higher economic growth is associated with higher GHG emissions on one hand and that the economic growth itself will reduce the environmental pollution (known as the Environmental Kuznets curve (EKC) hypothesis) on the other (see Hill and Magnani [4], Stern [5], Dinda [6] for detail review of EKC). Also, Dinda and Coondoo [7] argue that in order to maintain environmental quality, the developed countries have to forgo their income growth and the developing countries have to restraint their growth ambitions to reduce CO_2 emissions. Moreover, the Kyoto Protocol (1997) is highly criticized for the lack of inclusion of obligatory reduction of CO_2 emissions' by developing countries (Pittel and Rubbelke [8]) because participation of the economies such as India, China, Indonesia, and Brazil are crucial in solving the problem of international significance. Hence, investigation of causality relationships among CO_2 emissions, energy consumption and income are of utmost important in order to formulate strategies by specific countries to combat global warming and climatic instability. The relationships between these three are widely discussed in the literature but the results are inconclusive. Three viewpoints are dominant in the literature. First, a *neo-classical* view which states that income of a country can be 'neutral' to energy consumption and, therefore, the country can undertake energy conservation policy to reduce CO_2 emissions to combat environmental degradation, defined as the 'neutrality hypothesis'. Second, the income of a country could be highly linked with energy consumption and, therefore, like any other factors of production, the energy consumption can be a limiting factor to economic growth. For example, Stern [9,10] found that energy is a driving factor for economic development in the USA; which was echoed by Masih and Masih [11] for India, Wolde-Rufeal [12] for Algeria, Cameron, Congo DR, Egypt, Nigeria; Wolde-Rufael [13] for Shanghai; Soytas and Sari [14] for France, Germany and Japan; Chontanawat et al. [15] for Kenya, Nepal and the Philippines. In this view, reduction in energy consumption tends to reduce income and, therefore, energy conservation policy may be harmful to the economy. Third, the causality relationship between environmental pollution and income is widely debated over the past decades under the EKC hypothesis. The EKC hypothesis postulates that there is an inverse U-shaped relationship between income and environmental pollutions. It explains that environmental degradation initially increases with the increase in income, reaches a threshold point and then it declines with corresponding increased in income (Grossman and Krueger [16], Selden and Song [17], Stern et al. [18]). A major point to note that all of these views were developed based on a bivariate analytical framework of either energy consumption-income or environmental pollutions-income nexus. Recently some studies expanded the scope to a multivariate dimension: i.e., energy consumption, income and environmental pollutions. For example, Soytas and Sari [19] found that CO_2 emission Granger cause energy consumption in Turkey without any feedback. Similarly, income does not Granger cause CO_2 emissions in USA but energy does (Soytas et al. [20]) also echoed by Xing-Ping and Xiao-Mei [21] for China. An interesting result was found by Ilhan and Ali [22] for Turkey who used an auto-regressive distributed lag (ARDL) approach and concluded that that neither CO_2 emissions nor energy consumption Granger causes real income. However, the empirical evidence still remains controversial and ambiguous.

Given this backdrop, the main objective of this paper is to investigate a country specific dynamic causality relationship that combines income, energy consumption and CO_2 emissions under a single framework. This is because the empirical analysis at the aggregate level using multiple countries are so far unable to capture the complexities of the economic environment of each individual countries. Therefore, we postulate that a country specific case study will provide precise inferences on the issues we are investigating. Our choice of India as a case study is motivated by the fact that the country is the fastest growing economy next to China, currently the largest economy in the world (World Development Indicators (WDI) [23]). The growth rate of commercial energy consumption in India is 4.9% per annum during the period of 1965–2007. And both the income and CO_2 emissions have grown at a rate of 4.7% per annum during the same period (Balachandra et al. [24]). The main sources of energy are crude oil, natural gas and coal which accounts for 90% of total energy consumption. The country is the fourth largest total GHG emitter in the world although it is one of the lowest per capita emitter countries. The share of coal consumption to total energy consumption is increasing at the rate of 4.2% per annum which implies that the intensities of GHG emissions may increase as burning of coal is the main source of higher CO_2 emissions. Since the energy consumption is increasing faster, the dependence on energy from non-renewable sources can exert a fierce constraint if energy consumption and income co-move in the long-run. Therefore the country is in need of fixing a *'status quo'* target to reduce consumption of fossil fuels and stop CO_2 emissions which may have strong long-term implications for India and global level.

Other motivating factor is the commonly held view that reduction in GHG emissions may constraint economic growth. This may be a reason why India is strongly against the international pressure to make a commitment for legally binding agreement of its GHG emissions. Therefore, it is important to determine whether CO_2 emissions reduction could really undermine income growth in India, which may very well explain India's position on legally binding emission reduction commitments. To our knowledge, our paper is the first attempt to investigate the dynamic causality relationships in a multivariate framework which overcome the widely discussed problems of omitted variables bias and stationarity of selected variables in the estimation of bivariate modeling framework. The contributions of our study to the existing literature are two folds: (a) use of a multivariate framework of Toda and Yamamoto [25] hereafter TY model, i.e., energy – CO_2 emissions-income; and (b) use of additional variables, such as the labour force and fixed capital stock in the analysis. Hence, depending upon the causality relationships, India may resort to different strategies to fight against global warming and climatic instability. An additional contribution is that the TY model has some advantages over others when dealing with a finite sample as well, implying that it is unlikely to provide misleading inferences. The finding of this paper has strong policy implications for India as well as for the global level. Specifically, the policy makers in India are under pressure from the environmental delegates to cut emissions although the country still faces huge challenge to reduce its poverty level (currently about 29% of its population live below the poverty line – WDI [23]) requiring economic growth. Therefore, if income is associated with energy consumption (and energy consumption drives the economy) and energy consumption is associated with GHG emissions (and energy consumption drives GHG emissions) then policy makers in India faces a major *dilemma* because the environmental degradation through GHG emissions would aggravate the economy in the long-run, perhaps in the short-run as well. If the result is otherwise, then policy makers may place higher attention

to find alternative less polluting and renewable energy sources to meet increasing energy demands. In this way, India could become energy secured and GHG emissions itself will not be a constraint for long-term economic growth. The energy consumption and emissions reduction policy in India could also be a very good example for similar economies across the world.

The remainder of the paper is structured as follows. The next section presents a brief review of literature. Section 3 presents the data and methodologies. Section 4 presents the results and discussions. The section 5 concludes and draws policy implications.

2. Brief review of literature

The dynamic causality relationship between energy consumption-income and environmental pollution-income (under the EKC) has been well documented in the literature. The aims of these studies were mainly to describe the temporal relationships but largely with the application of bivariate models particularly for India (see Table 1). Yet, there seems to be no consensus regarding the dynamic causality relationship between energy consumption-income and environmental pollution-income. The plausible reasons of not having conclusive results may be due to misspecification of the estimated models, omitted variables bias, or failure to select true lag lengths (which are very sensitive to Granger non-causality). The existing literature in India shows mixed evidences and sometimes conflicting results even when using similar databases. Most of the studies dealt with the causality relationship between energy consumption and income. However, results from the literature can be broadly categorized into three different strands i.e., a unidirectional causality, a bi-directional causality and no causality at all. Ghosh [26] has investigated the causality relationship between CO_2 emission and economic growth and included as additional variables investment and employment. He has used the ARDL and Johansen model which has a low power in the test results in the case of small sample. Recently, some studies (for example, Soytas et al. [20], Soytas and Sari [19], Xing-Ping and Xiao-Mei [21]) have investigated the dynamic causality relationships among energy consumption-income-environmental pollution within a single framework applying the multivariate model of TY [25], multivariate Johansen and Juselius [27] error correction model (ECM) (Ang [28]) and panel cointegration (Apergis and Payne [29,30], Apergis et al. [31]). However, such an advanced application of TY modeling approach is non-existent for India which happens to be one of the top GHG emitters and also one of the top income growth and energy consumption growth countries in the world. Although it has been recognized that the interrelationships among the capital accumulation, environmental pollutions and other growth parameters are of central importance in the growth theory (Xepapadeas [32]), but there is a void in literature examining relationship between income, energy consumption, and CO_2 emissions which also included labour and fixed capital stock as additional variables under the same framework, specifically for India.

3. Data and econometrics methodology

3.1. Data

The study uses annual time series data for India which are taken from the world development indicator database (CD-ROM [23]) of the World Bank. The study uses real GDP (in 2000 constant prices), total commercial energy consumption (*kt* of oil equivalent), total carbon dioxide emissions (*kt*) and two additional variables, the total labour forces, the gross fixed capital formation (as a proxy for stock of physical capital) (in 2000 constant prices). The data are defined as follows: Y is for GDP, En is for commercial energy consumption, CO_2 is for carbon dioxide emissions, L is for labour forces and K is for gross fixed capital formation. All data are converted into natural logarithm and covers the period from 1971 to 2006 based on the times series data availability. There are some debates in the literature as to whether to use the total or per capita basis data. In a single country study, dividing the variables by the population number only scales the variables down (Soytas et al. [20]) with apparently no other advantage. Friedl and Getzner [45] further argue that the Kyoto Protocol calls for a reduction in the percentage of emissions from its base of total emissions rather than per capita emissions. Therefore, our study uses aggregate data rather than per capita data to estimate the dynamic causality relationships among CO_2 emissions, energy consumption and income in a multivariate TY model.

3.2. Time series properties of data

Before proceeding with estimating the TY model, the unit root test is required to obtain the maximum integration order of the variables. Therefore, we perform different unit root tests – the augmented Dickey–Fuller (ADF) [46], the Phillips–Perron (PP) [47] and the Zivot–Andrew (ZA) [48] to obtain robust results. The ADF test with an optimal lag length determined by the Schwarz information criteria (SIC) is used in the following specification:

$$\Delta v_{i,t} = c + \rho v_{i,t-1} + \sum_{j=1}^{k-1} \Gamma_i \Delta v_{i,t-j} + \beta T + \varepsilon_{i,t} \tag{1}$$

where $v_{i,t}$ are the respective variables (Y, En, CO_2, L and K), Δ is a first difference operator, T is the time trend and $\varepsilon_{i,t}$ denotes white noise error term. Eq. (1) tests the null of a unit root ($\rho = 0$) against a mean-stationary alternative ($\rho \neq 0$) The term $\Delta v_{i,t-j}$ is a lagged first difference to accommodate serial correlation.

When the time series data are subject to both a deterministic trend (T) and an exogenous shock that causes a structural break, the ADF test tends to under-reject (Phillips and Perron [47]). Therefore, we perform the presence of a unit root using PP in the following specification.

$$v_{i,t} = c + \beta \left\{ t - \frac{T}{2} \right\} + \rho v_{i,t-1} + \varepsilon_{i,t} \tag{2}$$

where $v_{i,t}$ is respective time series, $\{t - T/2\}$ is the time trend and where T is the sample size, $\varepsilon_{i,t}$ v_t is the error term. This procedure, in fact, uses a non-parametric adjustment to the Dickey–Fuller test statistics and allows for dependence and heterogeneity in the error term.

Moreover, we perform the ZA test to take the structural break into account. ZA tests consider one unknown structural break with a deterministic trend. We present the most restrictive model of ZA in which one can consider an unknown structural break both in intercept and in slope using following specification:

$$\Delta v_{i,t} = c + \rho v_{i,t-1} + \beta T + \theta DU_t + \gamma DT_t + \sum_{j=1}^{k-1} \psi_i \Delta v_{i,t-j} + \omega_{i,t} \tag{3}$$

where θDU_t is an indicator dummy variable for a mean shift occurring at each possible break-date (TB) while DT_t is the corresponding trend shift variable. Those are

$$DU_t = \begin{cases} 1 & \text{if } t \succ \text{TB} \\ 0 & \text{otherwise} \end{cases} \quad \text{and} \quad DT_t = \begin{cases} t - TB & \text{if } t \succ \text{TB} \\ 0 & \text{otherwise} \end{cases}$$

The null hypothesis is $\rho = 0$, which implies that the series $v_{i,t}$ contains a unit root with a drift that excludes any structural break, while the alternative hypothesis $\rho < 0$ implies that the series is

Table 1
Summary of causality test results of earlier studies.

Authors	Methodology used	Period	Main variables	Conclusions
Masih and Masih [11]	Johansen–Juselius, Variance decomposition	1955–1990	Energy consumption, real GNP	En → Y
Murray and Nan [33]	Granger causality	1970–1950	Electricity consumption, real GDP	ELC → ≠ Y
Cheng [34]	Johansen–Juselius	1952–1995	Energy Consumption, real GNP	Y → En
Asafu-Adjaye [35]	Johansen–Juselius	1973–1995	Commercial energy usage per capita, real GDP	CEN → Y
Ghosh [36]	Johansen–Juselius	1950–1997	Electricity consumption per capita, real GDP per capita	Y → ELC
Fatai et al. [37]	Johansen–Juselius	1960–1999	Energy consumption, real GDP	En → Y
Paul and Bhattacharya [38]	Engle–Granger, Johansen–Juselius	1950–1996	Energy consumption, real GDP	En ↔ Y
Lee [39]	Pedroni panel cointegration	1975–2001	Energy usages, real GDP	E → Y
Chontanawat et al. [15]	Johansen–Juselius	1971–2000	Energy consumption per capita, real GDP per capita	E → ≠ Y
Mahadevan and Asafu-Adjaye [40]	Pedroni panel cointegration, Johansen–Juselius	1971–2002	Energy usages per capita, real GDP per capita	E → Y
Huang et al. [41]	Dynamic panel estimation	1972–2002	Energy consumption, real GDP per capita	E→ ≠ Y
Jinke et al. [42]	Engle–Granger	1980–2005	Coal consumption, real GDP	CC → ≠ Y
Ghosh [43]	ARDL model	1970–2005	Crude oil import, income, price	Y → Import
Ghosh [26]	ARDL model, Johansen–Juselius	1971–2006	Carbon emissions, economic growth	CO_2 → ≠ Y
Yemane [44]	ARDL, Toda and Yamamoto	1969–2006	Economic growth, nuclear energy consumption	NEn ↔ Y

a trend-stationary process with one-time break occurring at an unknown point. The ZA test considers every point as a potential break-date (TB) and run the regressions sequentially. Among all TB, the procedure selects the TB which minimizes the one-sided t-statistic for testing $\widehat{\rho}(=\rho-1)=1$.

3.3. Econometrics methodology

The often used methodologies in the literature for testing causality are the standard Granger non-causality, causality in Johansen and Juselius [27] ECM, causality in ARDL model proposed by Pesaran and Shin [49] and causality in the TY multivariate model. The empirical evidence presented in our paper is carried out by using TY because of its advantages over others. The TY procedure is used even when the variables have a different order of integration. In the Johansen model, a pre-requisite is that the variables must be in the same order of integration. Toda and Yamamoto [25] showed that the pre-tests for cointegration ranks in the Johansen type ECM are very sensitive to the values of nuisance parameters in a finite sample. Hence, causality inference based on Johansen may suffer from severe pre-test biases. If the system contains unit root, standard Wald statistics based on OLS of level vector auto-regressive (VAR) model for testing coefficient restrictions have non-standard asymptotic distribution that may involve nuisance parameters (Sims et al. [50] and Toda and Phillips [51]). The augmented VAR model of TY on the other hand is much appealing because it can be applied for any arbitrary level of integration, $I(0)$, $I(1)$ or $I(2)$ and does not need to be in the same order of integration either. The TY procedure uses a modified Wald test (MWALD) for putting restrictions on the parameters of the VAR (k) from a augmenting VAR ($k+d^{\max}$) model, where k is the lag length and $d^{\max}$ is the maximum order of integration of variables. The novelty of the TY procedure is there is no loss of information due to differencing because it estimates a VAR in level. The model is valid until $k \geq d$ (Kuzozumi and Yamamoto [52]). Following Soytas et al. [20], Soytas and Sari [19], Xing-Ping and Xiao-Mei [21]; Mohammad et al. [53] we apply TY to examine the dynamic causality relationships among energy consumption, CO_2 emission and income in India.

The TY model can be written in a simpler form as following specification

$$v_t = \alpha_v + \varphi_1 v_{t-1} + \ldots + \varphi_n v_{t-n} + \omega_{v,t} \tag{4}$$

Table 2a
Unit root test results.

Tests → variables↓		ADF	PP	Decision	ADF	PP	Decision
		Level			First differences		
Drift (τ_u)	En	0.269 (0)	0.280 (2)	Non-stationary	−6.043*** (0)	−6.043*** (2)	Stationary
	Y	2.719 (0)	4.218 (4)	Non–stationary	−6.008*** (0)	−6.018*** (2)	Stationary
	CO_2	−1.339 (0)	−1.771 (7)	Non-stationary	−6.826*** (0)	−6.825*** (0)	Stationary
	L	0.402 (1)	0.663 (4)	Non-stationary	−2.337*** (1)	−3.878*** (3)	Stationary
	K	2.839 (0)	4.394 (10)	Non-stationary	−4.102*** (0)	−4.025*** (4)	Stationary
Drift and slope (τ_t)	En	−2.092 (0)	−2.192 (2)	Non-stationary	−5.947*** (0)	−5.948*** (2)	Stationary
	Y	−1.624 (0)	−1.624 (0)	Non-stationary	−7.195*** (0)	−8.506*** (5)	Stationary
	CO_2	−0.939 (0)	−0.766 (2)	Non-stationary	−7.178*** (0)	−7.528*** (5)	Stationary
	L	−2.301 (0)	−2.387 (4)	Non-stationary	−3.823*** (0)	−3.901** (3)	Stationary
	K	0.123 (0)	1.263 (8)	Non-stationary	−5.024*** (0)	−5.063*** (8)	Stationary

Notes: Lag length for ADF test is decided based on SIC and are in the parentheses; maximum bandwidth for PP test is decided based on Newey–West [58] and are the parentheses; *** and ** indicates that unit root tests are rejected at 1% and 5% level; τ_u and τ_t indicates *tau*-statistics of random walk with drift, random walk with trend, respectively; critical values are −3.633, −2.948, −2.613 at 1% and 5%, respectively in the case of only drift; −4.244 and −3.544 are at 1% and 5% level, respectively in the case of drift and slope; probability levels are based on MacKinnon [59].

The model in Eq. (4) can be written in following five different equations

$$\begin{aligned}\ln En_t &= \alpha_1 + \sum_{i=1}^{k}\varphi_{1i}\ln En_t + \sum_{j=k+1}^{d\max}\varphi_{2i}\ln En_{t-j} + \sum_{i=1}^{k}\gamma_{1i}\ln Y_t \\ &+ \sum_{j=k+1}^{d\max}\gamma_{2i}\ln Y_{t-j} + \sum_{i=1}^{k}\psi_{1i}\ln CO_2 + \sum_{j=k+1}^{d\max}\psi_{2i}\ln CO_2 \\ &+ \sum_{i=1}^{k}\zeta_{1i}\ln L_t + \sum_{j=k+1}^{d\max}\zeta_{2i}\ln L_{t-j} + \sum_{i=1}^{k}\varpi_{1i}\ln K_t \\ &+ \sum_{j=k+1}^{d\max}\varpi_{2i}\ln K_{t-j} + \omega_{1,t}\end{aligned} \tag{5}$$

$$\begin{aligned}\ln Y_t &= \alpha_1 + \sum_{i=1}^{k}\gamma_{1i}\ln Y_t + \sum_{j=k+1}^{d\max}\gamma_{2i}\ln Y_{t-j} + \sum_{i=1}^{k}\varphi_{1i}\ln En_t \\ &+ \sum_{j=k+1}^{d\max}\varphi_{2i}\ln En_{t-j} + + \sum_{i=1}^{k}\psi_{1i}\ln CO_2 \\ &+ \sum_{j=k+1}^{d\max}\psi_{2i}\ln CO_2 + \sum_{i=1}^{k}\zeta_{1i}\ln L_t + \sum_{j=k+1}^{d\max}\zeta_{2i}\ln L_{t-j} \\ &+ \sum_{i=1}^{k}\varpi_{1i}\ln K_t + \sum_{j=k+1}^{d\max}\varpi_{2i}\ln K_{t-j} + \omega_{2,t}\end{aligned} \tag{6}$$

$$\begin{aligned}\ln CO_2 &= \alpha_1 + \sum_{i=1}^{k}\psi_{1i}\ln CO_2 + \sum_{j=k+1}^{d\max}\psi_{2i}\ln CO_2 + \sum_{i=1}^{k}\varphi_{1i}\ln En_t \\ &+ \sum_{j=k+1}^{d\max}\varphi_{2i}\ln En_{t-j} + \sum_{i=1}^{k}\gamma_{1i}\ln Y_t + \sum_{j=k+1}^{d\max}\gamma_{2i}\ln Y_{t-j} \\ &+ \sum_{i=1}^{k}\zeta_{1i}\ln L_t + \sum_{j=k+1}^{d\max}\zeta_{2i}\ln L_{t-j} + \sum_{i=1}^{k}\varpi_{1i}\ln K_t \\ &+ \sum_{j=k+1}^{d\max}\varpi_{2i}\ln K_{t-j} + \omega_{3,t}\end{aligned} \tag{7}$$

$$\begin{aligned}\ln L_t &= \alpha_1 + \sum_{i=1}^{k}\zeta_{1i}\ln L_t + \sum_{j=k+1}^{d\max}\zeta_{2i}\ln L_{t-j} + \sum_{i=1}^{k}\varphi_{1i}\ln En_t \\ &+ \sum_{j=k+1}^{d\max}\varphi_{2i}\ln En_{t-j} + \sum_{i=1}^{k}\gamma_{1i}\ln Y_t + \sum_{j=k+1}^{d\max}\gamma_{2i}\ln Y_{t-j} \\ &+ \sum_{i=1}^{k}\psi_{1i}\ln CO_2 + \sum_{j=k+1}^{d\max}\psi_{2i}\ln CO_2 + + \sum_{i=1}^{k}\varpi_{1i}\ln K_t \\ &+ \sum_{j=k+1}^{d\max}\varpi_{2i}\ln K_{t-j} + \omega_{4,t}\end{aligned} \tag{8}$$

$$\begin{aligned}\ln K_t &= \alpha_1 + \sum_{i=1}^{k}\varpi_{1i}\ln K_t + \sum_{j=k+1}^{d\max}\varpi_{2i}\ln K_{t-j} + \sum_{i=1}^{k}\varphi_{1i}\ln En_t \\ &+ \sum_{j=k+1}^{d\max}\varphi_{2i}\ln En_{t-j} + \sum_{i=1}^{k}\gamma_{1i}\ln Y_t + \sum_{j=k+1}^{d\max}\gamma_{2i}\ln Y_{t-j} \\ &+ \sum_{i=1}^{k}\psi_{1i}\ln CO_2 + \sum_{j=k+1}^{d\max}\psi_{2i}\ln CO_2 + \sum_{i=1}^{k}\zeta_{1i}\ln L_t \\ &+ \sum_{j=k+1}^{d\max}\zeta_{2i}\ln L_{t-j} + + \omega_{5,t}\end{aligned} \tag{9}$$

Now we demonstrate how MWALD test works. For example in Eq. (5), we can test the hypothesis that CO_2 does not Granger cause energy consumption if $\psi_{1i} = 0 \forall_i$; similarly income does not Granger cause energy consumption if, $\gamma_{1i} = 0 \forall_i$; labour does not Granger cause energy consumption if $\zeta_{1i} = 0 \forall_i$; and capital does not Granger cause energy consumption if $\varpi_{1i} = 0 \forall_i$. In the similar way the Granger causality test can be performed for remaining equations from 6 to 9.

In short, the steps of TY procedure are as follows: (i) investigate the maximum order of integration, $I(d)$ of the selected variables by performing different unit root tests; we define it as $d^{\max}$ (ii) determining the optimum lag length, p, of a level VAR using different lag length criteria, (iii) estimating the augmented VAR $(p + d^{\max})$ in level as defined in Eq. (5) (iv) since the TY procedures is sensitive to the number of lag, therefore, checking the robustness of augmented VAR $(p + d^{\max})$ model by different diagnostic tests (v) performing a MWALD test on the first p parameters instead of all parameters in the augmented VAR model and ignore the coefficients of lagged vectors from $d^{\max}$ (Caporale and Pittis [54]), the statistics follow an asymptotic Chi-square distribution (Zapata and Rambaldi [55]).

3.4. Generalized impulse response function (GIRF)

The TY results give the long-run Granger causality within the sample period but it does not allow to gauge relative strength of causality in an out-of-sample period. In contrast, the innovation accounting method, the GIRF, shows how a variable responds from a shock in other variables and whether shock persists or dies out over time. However, the paper uses a GIRF proposed by Koop et al. [56], and Pesaran and Shin [49] as this approach has the advantages over the standard impulse response function (Ewing and Payne [57]) in a way that these approaches are invariant to the Cholesky ordering of the variables enter into VAR. The GIRF function starts with the following vector auto-regressive moving average

$$V_t = \sum_{j=0}^{\alpha} A_j U_{t-j} + \varepsilon_t \tag{10}$$

Here, V_t is an (5×1) vector of the variables, $A_j = \Phi_1 A_{j-1} + \Phi_2 A_{j-2} + \cdots + \Phi_p A_{j-p}$, $j = 1, 2, 3 \ldots$ with $A_0 = I_n$ and $A_j = 0$ for $j < 0$. The generalized impulse response (G) for a shock to the entire system ε_t is defined as:

$$G_x = E\left(\frac{V_{t+n}}{U_t = U_t; \Omega_{t-1}}\right) - E\left(\frac{V_{t+n}}{\Omega_{t-1}}\right) \tag{11}$$

Here, the process up to period $t-1$ is known and is denoted by information set Ω_{t-1}. The generalized response for V_t with respect to a shock in the j-th equation is given by

$$GI_z, J(n) = \beta' B_n \sum \frac{e_j}{(\delta jj)^{1/2}}, \quad \text{where } n = 0, 1, 2 \ldots \tag{12}$$

Table 2b
Unit root test results of ZA.

Variables	Level	Break	Decision	First differences	Break	Decision
En	−3.103 (c)	1988	Non-stationary	-5.293^{**} (a)	2001	Stationary
Y	−2.623 (c)	1979	Non-stationary	-5.129^{**} (a)	1991	Stationary
CO_2	−4.547 (c)	1996	Non-stationary	-5.133^{**} (a)	1985	Stationary
L	−3.086 (c)	1995	Non-stationary	-5.723^{**} (a)	1981	Stationary
K	−2.813 (c)	2002	Non-stationary	-4.832^{**} (a)	2002	Stationary

Notes: Break denotes the time of structural break, ** indicates significance at 5% level, critical values are −5.570 and −5.080 at 1% and 5% significance level; a means break only in drift and c means break both in drift and slope.

Table 3
Diagnosis test results of VAR (2).

Diagnosis tests	Test statistics	*p*-values
J–B test (Doornik–Hansen)	13.291	0.2078
Autocorrelation LM	34.212	0.1034
White heteroskedasticity	490.330	0.201
VAR stability	No root lies outside the unit circle	–

Notes: J–B test null is residual normality, autocorrelation LM test null is no serial correlation up to selected lag, ARCH (auto-regressive conditional heteroscedasticity) test null is no ARCH effect up to selected lag, white heteroskedasticity test includes cross terms and the null is no heteroscedasticity, VAR stability reveals that all roots have modulus less than one and lie inside the unit circle.

Here B_n is the cumulative effective matrix, e_j is a selection vector, and $(\delta jj)^{1/2}$ denotes one standard error shock.

4. Empirical results and discussions

4.1. The unit root test results

The unit root test results are reported in Tables 2a and 2b. The unit root results confirm the maximum order of the integration for the selected variables is 1 which is necessary for TY procedures of Granger non-causality analysis. The ADF, PP and ZA tests confirm the same conclusion indicating that our results are robust. Having determined $d_{\max} = 1$, we proceed to determine the true lag length k.

Next, for determining the optimum lag length we follow Lutkepohl's [60]. We have checked all criteria including likelihood ratio (LR), final prediction error, Akaike information criteria, SIC, and Hannan-Quinn. Irrespective of the number of maximum lag, we find that SIC consistently shows optimum lag to be 1 but in all other criteria the optimum lag length vary with varying maximum lag length. Therefore keeping the small sample in mind, we have decided to accept the optimum lag length to be 1. To complement our decisions we have checked all diagnosis tests and we have not found any violation. Given both the maximum order of integration ($d_{\max}$) and the optimum lag length (k) to be 1, we have estimated the augmented VAR ($k + d_{\max}$) in level, that is – VAR (2) for Granger non-causality test including trend and quadratic trend as exogenous in level VAR (2). We have checked the VAR stability condition and have found that no roots are outside of the unit circle. Table 3 shows the results of diagnosis check for the estimated VAR (2) and indicates that there are no problems of non-normality, autocorrelation and heteroskedasticity. Recall that before proceeding to test the Granger non-causality we are subject to check the diagnosis results for all equations of endogenous variables in VAR (2) what we do next.

The diagnostic results are presented in Table 4. The B–G test results suggest that there is a serial correlation problem only in the CO_2 equation but the Correlogram and the squared Correlogram shows no problem of serial correlation for this. Apart from that, VAR (2) is used when a system failed to accept the null hypothesis of serial correlation (see Table 3). The Ramsey RESET tests show that there is a problem only in equations L and K, but on the other hand, CUSUM tests do not show any evidence of instability (CUSUM square show the same but the test results are not presented here because of brevity). Apart from that, VAR system shows stability as all roots lie within the unit circle. Given all of these diagnostic test results from level VAR (2), we safely proceed to test Granger non-causality with MWALD test.

4.2. Granger causality test results

Results of the estimated Granger causality test are presented in Table 5. As we are more interested on the variables income, energy consumption and CO_2 emissions we concentrated on explanations for these variables. We find a very interesting result in case of energy consumption and income. There is no causality relationship between the two in either direction which means that energy consumption does not drive the income in India at all and income level does not proceed to energy consumption. The *neo-classical view* supports our results that energy consumption can be neutral to the economic development. Therefore, the government of India may follow energy conservation and energy efficiency policies without limiting income growth potential. A possible explanation

Table 4
Diagnosis test results of estimated endogenous equations.

Equations	J–B test	B–G test	ARCH-LM test	White test	Ramsey RESET	CUSUM test
En	4.589	5.596^{*}	0.676	9.501	2.609	Within
	(0.102)	(0.061)	(0.411)	(0.659)	(0.106)	
Y	1.817	0.949	1.456	6.459	1.976	Within
	(0.403)	(0.622)	(0.227)	(0.891)	(0.159)	
CO_2	0.919	6.334^{**}	0.238	16.348	0.919	Within
	(0.632)	(0.042)	(0.625)	(0.176)	(0.338)	
L	0.186	3.854	3.199^{*}	16.904	20.376^{***}	Within
	(0.911)	(0.146)	(0.074)	(0.153)	(0.000)	
K	0.587	1.812	0.777	12.197	3.963^{**}	Within
	(0.746)	(0.404)	(0.378)	(0.430)	(0.047)	

Notes: ***, ** and * indicates the significant level at 1%, 5% and 10% level, respectively; the probability level are in the parentheses; J–B test is for null of normality, B–G test null is no serial correlation up to the selected lag, ARCH test null is no ARCH effect up to selected lag, White test null is no heteroscedasticity), Ramsey RESET test (with one fitted term) null is no specification problem using LR, CUSUM test is based on the cumulative sum of the recursive residuals that explains parameter instability if the cumulative sum is not within the band of two critical lines at 5% significance level.

Table 5
Granger causality results.

Dependent variables	MWALD test					Causality inference
	En	Y	CO_2	L	K	
En	–	2.242 (0.134)	4.919** (0.027)	1.735 (0.188)	1.372 (0.241)	En ← CO_2
Y	1.955 (0.162)	–	0.013 (0.909)	1.1782 (0.278)	4.438** (0.035)	Y ← K
CO_2	3.481* (0.062)	0.671 (0.413)	–	0.7220 (0.396)	10.969*** (0.001)	CO_2 ← En CO_2 ← K
L	0.279 (0.597)	0.519 (0.471)	2.400 (0.121)	–	4.909** (0.027)	L ← K
K	1.694 (0.193)	0.474 (0.491)	0.299 (0.584)	2.049 (0.152)	–	–

Notes: ***, ** and * indicates the significant level at 1%, 5% and 10%, respectively; the probability level are in the parentheses; ← denotes a uni-directional causality.

is that the economic growth in India is largely supported by economic growth of services which may rely less on energy sources than some other parts of the economy. In addition, other factors of production might be more limited currently. For instance, the growth of the agricultural sector depends probably more on water supply than the increase in the use of energy.

Our result is different from the existing results in the literature for India, and also from those who followed bivariate models except Chontanawat et al. [15] and Huang et al. [41]. However, Soytas and Sari [19] found similar result for Turkey. Furthermore, Xing-Ping and Xiao-Mei [21] found that there is a uni-directional causality running from income to energy consumption in China but without any feedback implying that energy consumption is neutral to income, found in Turkey and India. The dynamic panel data model estimation by Bwo-Nung et al. [61] also reports similar findings, i.e., in the group of low income country, there is no causal relationship between energy consumption and income. However, for the middle income country, income drives energy consumption but the opposite does not hold true. We argue that our inferences are more reliable as our approach overcomes the inherent problems associated with bivariate modeling explained earlier.

Another important result is the existence of a bi-directional causality between energy consumption and CO_2 emissions. It is straightforward and intuitive that energy consumption drives CO_2 emissions because the main source of emission is the combustion of coal dominated fossil fuels in India. But probably the most interesting result is that the opposite also holds true. The unidirectional causality from energy consumption to CO_2 emissions is also straightforward because the energy supply of India relies currently very heavily on CO_2 emitting sources. Given the current technology, it seems that energy conservation is the best option for reducing emissions and the impact on global warming control. Since, energy consumption is neutral to income; energy conservation will not undermine income but would rather combat CO_2 emissions in India.

We do not find any evidence of causality relationship between income and CO_2 emissions in either direction which, however, differs from Dinda and Coondoo [7] but similar to Soytas et al. [20] for USA, Soytas and Sari [19] for Turkey, Xing-Ping and Xiao-Mei [21] for China. The similar result is also found by Ghosh [26] using ARDL model. This result indicates that income growth does not have a positive or negative impact on CO_2 emission. In terms of the EKC this could imply that India is at the turning point from moving an

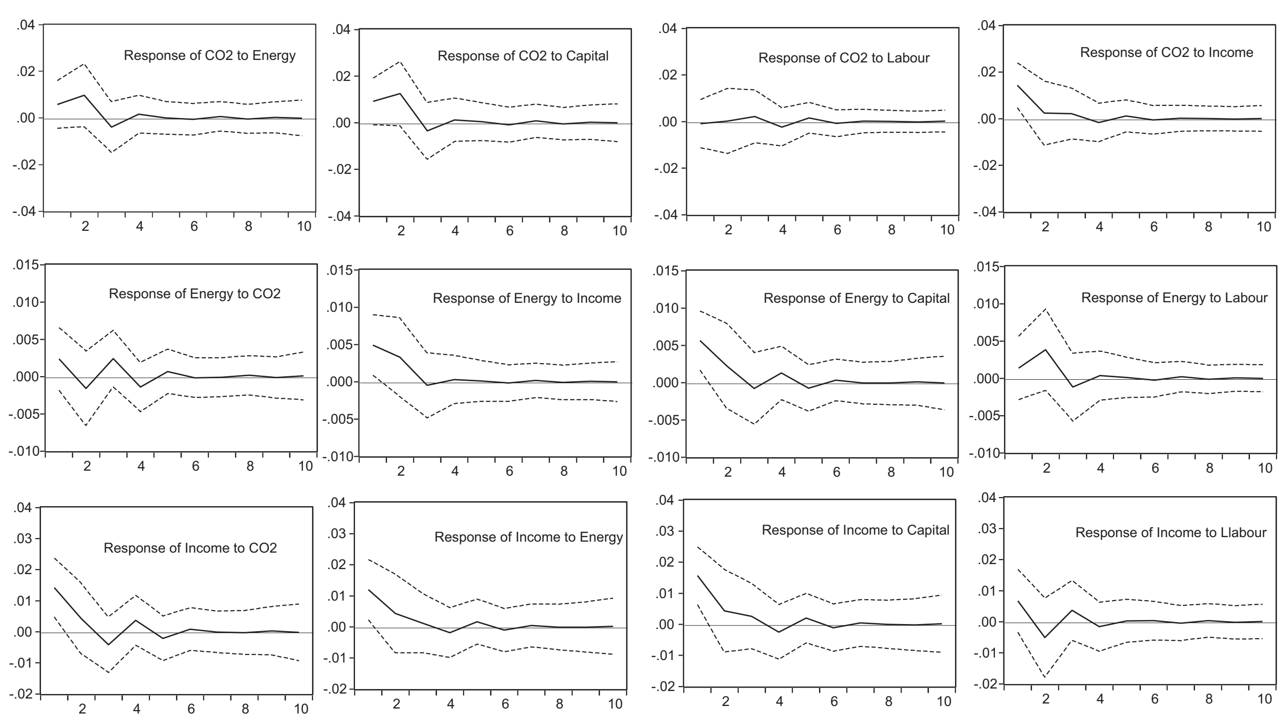

Fig. 1. Generalized impulse response function.

economic growth with a negative impact on environment to economic growth combined with reduced environmental impact. The result has strong policy message. The reluctance of the Indian policy makers to sign up for legally binding environmental abatement policy for the fear of declining economic development seems to be either a fallacy or may be due to a lack of clear evidence. Our findings are complimentary to the findings of China, Turkey and USA. Since income does not proceed CO_2 emissions in the long-run, as observed in China, USA and Turkey, India could very well reduce CO_2 emissions without affecting its income growth potential and may contribute significantly to combat increasing global warming problem.

4.3. Generalized impulse response function (GIRF) results

After examining the existence of causality between the energy – CO_2 emissions – income nexus, we have estimated a GIRF to determine the profile of macroeconomic variables and its response to shock in innovations. The significance is determined by using robust confidence interval presented with dotted lines. The standard errors are obtained by using a Monte Carlo simulation with 5ooo replications. Since our main goal is to see the response of CO_2, energy consumption and income from a standard deviation shock in the innovations of all endogenous variables, we present the results of responses only for these variables.

Fig. 1 shows the response of CO_2 emissions, energy consumption and income from one standard deviation shock in the innovations. Because of the structure of dynamic VAR, a shock to a variable not only directly affects itself but also to all other variables in the VAR. Fig. 1 provides the evidence that eventually the coefficients of impulse responses converge to zero or dies out over time. This indicates the stability of our estimated model. From the upper panel, all the initial impacts are positive; CO_2 emissions response from a shock in energy consumption and capital which is, however, similar to the long-run Granger causality but it is evident that CO_2 emission responds from a shock in income. In all cases the impact dies out within 4–5 years. The GIRF results support the results of Granger causality. Although it becomes insignificant within 4–5 years, there is an evidence of an interaction between income and CO_2 emission. Recall that the causality is absent in the long-run. The middle panel reveals that energy consumption responds to shock in all other variables positively and dies out within 4–5 years period. The response of energy consumption to income is relatively shorter but the response of energy consumption to CO_2 stays slightly longer. Here one interesting result is the response of energy consumption to income although our long-run causality indicates absence of causality, implying that income may drive higher energy consumption in the short-run. The third panel shows similar results but again income responds to energy consumption. Here we find the responses of income to CO_2 emission again. The GIRF provides evidence of the causality between income versus energy consumption and income versus CO_2 emissions which are, however, absent in the long-run. Therefore, energy consumption and the policy of reducing CO_2 emissions may have an impact on the income level of India only in the short-run.

5. Conclusions and policy implications

The present study investigates dynamic Granger causality relationship among energy consumption, CO_2 emission and economic growth in India with an advanced multivariate modeling approach (TY) thereby overcoming problems of omitted variables bias and uncertainty on the stationarity properties of the time series variables. We have also estimated the GIRF which overcomes the problems of Cholesky ordering of the variables. Our main results are as follows

(i) There is no long-run causality relationship between income and CO_2 emissions but in the short-run causality exists. The result is, however, probably goes against the EKC. This means that India does not need to compromise with its income growth in the long-run to reduce CO_2 emissions but in the short-run India may face such a constraint.
(ii) In contrast, there is a Granger causality running from energy consumption to CO_2 emissions with a feedback both in the long-run as well as short-run which indicates that the energy supply of India relies heavily on follow fossils based energy. An adaptation of the energy supply technology would be necessary to combat CO_2 emissions.
(iii) There is no causal relationship between energy consumption and income in the long-run but GIRF suggest that causality exists in the short-run which means that it is not energy that drives the economy or vice versa in the long-run but it does in the short-run.

The policy messages are clear. Since energy consumption in India is mainly based on the use of coal dominated fossil fuels, the country could follow energy conservation and energy efficiency polices without undermining long-run income growth. In this way India can combat CO_2 emissions, a dominated GHG gas mainly responsible for global warming and climatic instability. The country may set a '*status quo*', a target to cut CO_2 emission level which would have an indispensible contribution to the global emissions reduction campaign and contribute positively to solve the global warming problem.

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